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Financial Services to the Unbanked: the case of the Mzansi intervention in South Africa

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ABSTRACT

The Mzansi intervention is a major initiative designed to provide banking services to the unbanked South African population. This study investigates the underlying variables that define the choice of a Mzansi account from a consumer perspective. Unlike previous studies, we do not assume that demand for financial services is a given but instead that it is underlain by perceptions and attitudes. Financial attitudes and perceptions are found to exert significant effects on financial choices. In particular, aspirations and forward-looking values are instrumental in facilitating access to finance.

KEY WORDS: access to finance; variable selection; adaptive LASSO

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Introduction

The lack of financial access by the majority of the population in developing countries is a significant concern. Because it may not be possible to directly observe the latent demand for financial products, supply-side constraints have thus far dominated the discussion. There is, however, another much more entrenched belief that "those who have access but choose not to use services pose less of a problem for policymakers" (Beck & Demirguc-Kunt, 2008). Over the years, through a coordinated effort, the barriers to access have been considerably lowered in many developing countries. Relaxing the supply-side barriers brings the potential lack of demand for financial services to the forefront with important policy implications. Hence, studying the determinants of demand for financial services becomes an important research question.

The demand determinants define both the opportunities and the limitations of coordinated policy interventions designed to bring financial services to the needy. In this paper, we will examine a policy initiative, namely, the Mzansi intervention in South Africa, aimed at providing access to a basic pre-entry level of banking account for individuals who were previously excluded from the formal financial system. We investigate the drivers defining the uptake of Mzansi based on the genuine observed behavior of individuals and relate these results to their characteristics, attitudes and motivations. Section 2 discusses the features of the Mzansi account in detail, followed by a conceptual discussion in Section 3. Section 4 discusses data and methodology, followed by a discussion of the results in Section 5. Section 6 presents conclusions.

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2. Mzansi Account

Basic or entry-level bank accounts designed to promote financial inclusion have been introduced in many countries, and the South African approach is unique in several aspects. First, it is based on a risk-sharing coordinated intervention that draws on a linkage between private commercial banks and a state-owned bank. Second, the framework for this intervention is based on a voluntary financial agreement among the participating institutions. In South Africa, the exclusion from financial services was combined with racial discrimination, compounding the effects of poverty (Meagher and Wilkinson 2002). In this context, the issue of access to finance is no longer confined only to the issues of poverty and social disadvantage but becomes mixed with race and hence acquires a particular politically sensitive significance.

The 'Mzansi' account was initiated in 2004 to offer entry-level accounts, following the Financial Service Charter (FSC) policy recommendations. The Mzansi initiative is the main means by which the four large private banks (Absa, Nedbank, First National and Standard; together account for approximately 84 percent of the South African banking market) apply these recommendations but also includes a government-owned institution (Postbank), which is not a formal signatory of the Charter. The intervention was situated in the broader context of financial services outreach: scale (number of clients), depth (targeting poorer clients), scope (wide range of products/services) and breadth (clients with different socio-demographic characteristics).

The Financial Service Charter (FSC) is a voluntary agreement, a form of social contract among the main private banks in South Africa that are committed to expanding access and providing affordable financial services to the wider population. Motivated by the broader government policy framework of economically empowering the black community in South Africa, the FSC aimed to provide financial services and facilitate effective access to transactions and savings.

The FSC established a specific target for the participating institutions in terms of depth of outreach. Its aim was that 80 percent of the fifth segment of the South African living standard population should have effective access to transaction and savings products and services. Bearing in mind the commercial nature of the initiative and the potential longer-term profitability of the targeted population and hence the intended sustainability of the intervention, it appears that the concerns regarding whether there is sufficient effective demand for the offered financial service may not be as serious.

There have been, however, a large proportion of dormant accounts (Bankable Frontier Associaties, 2010), a fact that underlines the importance of examining what defines demand for Mzansi. Bankable Frontier Associaties 2010 notes that the number of Mzansi accounts opened between October 2004 and December 2008 was 6.0 million. However, there have been threats by some of the issuing institutions to drop out of the collaborative initiative. Furthermore, a significant proportion (42 percent) of the accounts are inactive.

In this paper, we concentrate on the demand-side issues pertaining to the choice of Mzansi. We investigate the inherent motivations in choosing a financial service. In particular, we look at the financial education background (how financially literate they are), opinions on their financial needs, aspirations and attitudes. Our central research question is as follows: in what way do these hidden factors (education, perception and attitudes) affect the uptake of the Mzansi account?

3. Conceptual Framework

Until recently, most analytical attention in the discourse on access to finance has focused on supply. there is ample evidence of what supply-side conditions (product design, market conditions and regulation) are required for expanding access to financial services (Beck, Demirguc-Kunt & Honohan 2009; Claessens, 2006). The implicit assumption of existing actual demand for financial services has lately been questioned (Anand & Rosenberg, 2008). More recently, financial inclusion studies have started to dedicate an increasing amount of analytical attention to the demand-side factors (Bauer, Chytilova, & Morduch, 2012; Cole, Sampson, & Zia, 2011). The common thread in such studies is the impact of psychological and subjective factors such as, e.g., self-discipline based on present bias theory (trade-off between current and future preference), financial perceptions, and behavior and attitudes toward financial access and inclusion. Altman (2012) provides an exhaustive overview of the two main strands in behavioral economics (Simon-March and Kahneman-Tversky). Both these strands provide support for our argument that perception and attitudes matter, but they present entirely different interpretations and often lead to contrasting conclusions. The main difference is that the Kahneman-Tversky tradition assumes these effects to be stable psychological errors that hence cannot be eliminated, while the Simon-March approach views them as rational adaptations based on particular interpretative frameworks that can be modified via learning. The Kahneman-Tversky tradition of learning biases is by far the more popular one, being incorporated into the mainstream. Concerning access to finance, for instance, Ito and Kono (2010) employ prospect theory, while Dupas and Robinson (2013) use mental accounting to explain behavior and constraints on finance. Karlan and Morduch (2010) state that " access to capital can be powerful for some yet not yield high returns for all", concluding that mechanisms matter. The specific reasons Karlan and Morduch (2010) list are limited self-control, loss aversion and mental accounting, which all fit the Kahneman-Tversky approach, leading to the conclusion that financial products need to be designed to fit the imperfect but stable processing frames of the potential customers. Interestingly, if one adopts the alternative Simon-March view, the above conclusion still stands, but the possibility of changing economic behavior by affecting the interpretative frameworks of customers is an open possibility.

The main theme running through the recent literature on social and psychological factors in access to finance is that they matter, either directly or as modifiers of known economic factors. For example, Fafchamps et al. (2011) show that capital does not affect women in the same way as men, while Lusardi and Mitchell (2013) establish that financial literacy (which is a well-established determinant of financial choices) correlates with security (risk) clustered by age, education, gender and ability. Financial literacy has been shown to depend upon social interaction and social networks (Bönte & Filipiak, 2012). In particular, choices can be defined by awareness because not being aware of certain options can preclude choosing them (Bönte & Filipiak, 2012). The latter supports the bounded rationality approach of Simon-March rather the biases than explanation of Kahneman-Tversky, particularly as Bönte and Filipiak (2012) emphasize the importance of word of mouth learning. The role of financial literacy can also be indirect as in Hastings, Madrian and Skimmyhorn (2013), who link financial literacy and planning. The role of subjective variables in defining economically important choice determinants can be further exemplified by Bauer and Chytilová (2009) who found that personal characteristics can predict a discount rate e.g., self-employment (riskier income) is associated with more impatience. Similarly, they find gender and age differences in that old people (and women) discount more heavily, as well as that social arrangements and education also have an effect. Hence, because discount rates feed into choices, socially conditioned and behavioral constraints would affect them. Dohmen et al. (2010) establish the link between risk aversion and discounting on one hand and cognitive ability on the other, i.e., the way things are viewed and understood affects choices. More general 'social' effects also feed into the same vein, e.g., de Janvry, Cai and Sadoulet (2012) discuss the effect of social networks (and information flows in particular), while Feigenberg, Field and Pande (2013) emphasize that social interaction can yield returns.

The role of behavioral and attitudinal constraints on financial decision-making has not been explored in detail. Initial evaluations of the Mzansi intervention have focused on directly asking clients about their opinion and attitudes. Thus, we know what socio-demographic characteristics the Mzansi account holders possess and their declared intentions (Bankable Frontier Associaties, 2010). The mode of elicitation of their motivation, however, could condition their stated opinion. To better understand what truly makes a customer choose a Mzansi account, one needs to dig deeper. Hence, instead of simply analyzing the differences between Mzansi holders and non-holders, it is preferable to investigate the choice of Mzansi conditional on their background. Conventional financial wisdom states that the relevant background variables are the ones measuring who they are. When access to financial services is concerned, these variables include financial literacy, i.e., is the elements of their financial 'education' and understanding of financial concepts. These elements will differentiate the actual from the stated scope of the Mzansi intervention. In simple words, we conceptualize the issue of access to financial services in the following way. Individuals require certain product because they believe it meets their needs. In this work, we do not place any restrictions on such beliefs, in that we do not require them to be rational or true. Then, an individual requires a service not because of their particular background (e.g., age or whether they are married) but because they think (wrongly or rightly) that they need it. Such beliefs will be measured by perceptions, opinions and attitudes. Conditioning economic action upon beliefs is nothing radically new: economic performance has long been known to depend on variables such as trust (Foss, 2012; Hunt, 2012) that can be viewed as a manifestation of beliefs.

It would have also been reasonable to expect that the background variables would contribute to forming these beliefs. This expectation, however, will result in a much more complex hierarchical representation of the decision process. In this paper, we simplify this scheme by only considering the beliefs to identify which behavioral attitudes and values are important in this decision. Once these attitudes and values are determined, the formation process of such attitudes can be explored, including the relevant background variables. Another justification for this approach is the finding of Cole et al. (2011) that while financial literacy has a significant effect on the uptake of financial services, financial education programs do not appear to show any discernible effect. Additionally, while such findings could be due to existing learning lags, they nevertheless demonstrate that personal values and beliefs are relatively stable constructs and can therefore be used to investigate actual behavior.

4. Data

This paper relies on the nationally representative 2007 FinScope South Africa dataset, created by a stratified and multistage sampling technique. The FinScope study was launched by FinMark Trus in 2003 in an attempt to establish credible benchmarks for the use of and access to financial services in South Africa (Bankable Frontier Associates, 2010). The aim was to achieve a measure and understanding of consumer demand across the transactions, savings, credit and insurance categories. The sample frame of the FinScope data consists of all South Africans aged 16 years and above. The 2007 FinScope dataset was collected from 3900 households using face to face interviews from April to May 2007. The scope of the data was categorized under two broad headings, namely, living standards and financial services. The former captures issues such as income, quality of life, and household demographics, while the latter tracks national financial access patterns and pathways in terms of products, service providers and household financial decisions and perceptions. We primarily use data from the second heading.

In particular, we use 102 variables measuring different finance-related attitudes and beliefs. These variables are grouped into the following categories: basic literacy, understanding financial terms, targets for financial advice, financial education desired and financial perception. As explained above, we expect that financial perceptions and attitudes affect the demand for Mzansi. There is, however, uncertainty about exactly which values and attitudes determine financial choices. It is therefore advisable to take a more exploratory stance and not simply investigate how such attitudes impact financial choices but also try to identify which variables have an impact. For this reason, we used all potential measures that we could identify in the dataset that could potentially fit into our conceptual framework. The full list of variables and their descriptions is available upon request. Providing it here would, however, be inappropriate due to the length of the list. Another universally acceptable practice is to provide some summary statistics for the data. Such an approach would also be impractical. Furthermore, the variables used are essentially indicators, and as such, their summary statistics are not particularly illuminating. One needs, nevertheless, some overview of what these variables are. Table 1 provides an overview of the categories in which these variables are grouped. Here, we will only briefly describe these categories to facilitate the discussion of the results. The understanding of the financial terms category includes 17 variables that quantify whether the respondents comprehend the actual meaning of a number of financial terms, ranging from simple ones such as bad debt and loans to increasingly more complex ones such as pieces of financial legislation. In principle, these variables can be considered to have a natural ordering. One could hypothesize that clients would need some basic financial understanding to select themselves into the Mzansi intervention, but having better understanding would mean that they would not be satisfied with the basic features offered by Mzansi and would require more sophisticated products.

Table 1. Variables overview

Variable Category	Number of variables
Basic Literacy	1
Understanding of financial terms	17
Targets for financial advice	15
Financial education desired	16
Financial perceptions grid 1	28
Financial perceptions grid 2	25

The target for the financial advice category includes 15 variables asking whether the respondents would use certain sources of financial advice. The sources range from informal ones (such as family and friends) to formal professional type of advice providers (such as financial institutions and independent brokers). This category complements the financial education variables in that it measures certain attitudes towards finance. It demonstrates the confidence respondents have in their own understanding of financial matters but also measures their attitude and trust in different sources of financial advice. It is difficult to elaborate on what one should expect with respect to this category because there does not seem to be a clear hierarchy in the ordering of the financial advice sources. Furthermore, some of the sources could be formulated in such a way that respondents may not properly understand them, and/or different types of advice sources could be bundled into the same category (for example, "A financial advisor other than an independent broker (e.g., tax consultant, auditor)").

A further 16 variables describe what type of financial education the respondents desire. These variables measure their intrinsic aspirations to further themselves. This category complements the financial education category in a very important and significant way. People aspiring to obtain further financial education could aspire to move up the financial access ladder. Therefore, even if their background (financial education) places them on a particular step of this ladder, their aspirations may motivate them and provide an incentive to move up. In this way, they may arrive at a higher step simply because it is where they (aspire to) belong. Hence, this category measures and quantifies the inherent motivations of banking clients. With respect to Mzansi, which is essentially a pre-entry level account, one could hypothesize that most types of expressed desire to obtain further financial education would move clients up towards the banks' entry level accounts and hence have a negative impact on Mzansi uptake.

Finally, we have two categories of financial perception variables. These questions ask people whether they agree with certain statements. In this way, the internal motivations and perceptions towards financial behavior are evaluated. The financial perceptions grid 1 variables ask factual questions about actual behavior, while grid 2 variables refer mostly to attitudes (opinion, trust and so forth). Thus, the two categories of financial perceptions complement each other by measuring two facets of the same phenomenon.

5. Methodology

In this particular study, we face a problem of an uncertain underlying relationship. We have identified potential determinants of the choice of Mzansi in terms of perceptions and attitudes. An inspection of the database provided us with 102 potential determinants. Unfortunately, this information still does not identify which of these potential determinants should be included in the model and which should not, which becomes an important research question in itself. We therefore face a not so uncommon situation of having a potentially large number of explanatory variables to be included in a model. Then, the questions of primary interest are which variables are to be included in the model (variable selection, model selection), and what are the parameters pertaining to the variables that belong to the model (model estimation).

Before proceeding to the variable selection issues, however, we need to specify candidate models. A binary dependent variable type of model is a natural choice for the modeling framework of the decision to choose a financial service (Mzansi in this case). In particular, the logistic regression is a common choice for a modeling framework in such situations. Logistic regression belongs to the class of generalized linear models (McCullagh & Nelder, 1989).

The next step is to find a method that can select which variables to include in the model. Unfortunately, estimating a 'grand' regression with all candidate variables and somehow restricting it is not a viable option. Similarly, Bayesian (or frequentist) model averaging procedures (as e.g., Białowolski, Kuszewski, & Witkowski, 2012) are computationally too expensive, and although they provide useful measures of model uncertainty, the latter can be difficult to interpret. The standard tools for statistical inference of regression results, such as t statistics and F tests, are based on the implicit assumption that the set of predictors is fixed in advance, which is, however, not the case here. We need to choose this set adaptively, using some formal (e.g., stepwise regression and all-subsets regression) or informal (e.g., researcher selecting variables that provide good fit) procedure. Under the adaptive selection of regressors, the classical tests are biased and therefore unreliable tools, resulting in wrong models and erroneous inference. Because the above variable and model selection procedures are based either directly on the F statistics or some related statistics, they will be biased. Two possible strategies can be used to circumvent the above problem. One is to apply bias-reducing adjustments to sequential F tests in an adaptive variable selection algorithm. The other option we will follow here is to implement a totally different approach to variable selection, namely, a regularization estimator.

In this paper, we apply what is most likely the best known and most popular regularization estimator, namely, the adaptive LASSO. Tibshiranni (1996) introduced the least absolute shrinkage and selection operator (LASSO) as a method that can simultaneously achieve both parameter estimation and variable selection initially in a linear model setting. In simple terms, LASSO is calculated by minimizing the relevant empirical risk function subject to the constraint that the $L1$ norm of the regression coefficients is bounded (by a given positive number). An equivalent and much more popular way to define the LASSO estimator is as a penalized estimator, in which the relevant empirical risk function is augmented by a penalty term proportional to the $L1$ norm of the regression coefficients. Formally, the LASSO can be expressed as follows:

$$\hat{\beta}(\lambda) = \arg\min_{\beta} \left\{ \ell(\beta) + \lambda \sum_{j=1}^{p} \left|\beta_j\right| \right\},$$

where $\ell(\beta)$ is the corresponding loss function (in this case the negative log-likelihood for the logistic regression model), p is the number of parameters (to be estimated), and λ is the penalty applied to the $L1$ norm of the coefficients. The penalty term shrinks the coefficients towards zero. Larger penalty terms achieve greater shrinkage, while smaller penalties induce less shrinkage. Unlike the ridge estimator (which uses an $L2$ norm penalty), the LASSO achieves sparse solutions, (i.e., some coefficients become exactly zero), which is a useful property when variable selection is desired. The presence of the penalty term in the optimization problem above introduces some bias but reduces the variance of the estimator, hence triggering the variance-bias trade-off, which effectively depends on the choice of the penalty term (i.e., λ). Different methods for such choices have been suggested in the literature. Here, we will use cross-validation.

Consequently, this method has been studied and extended (Fan & Li, 2001; Wang, Li, & Tsai, 2007). Although consistent in terms of variable selection in that it retains the important variables, the original LASSO estimator applies a fixed amount of shrinkage to all coefficients, which can be a problem when the so-called oracle property is desired. In particular, the LASSO estimator can be an oracle only under certain special circumstances subject to non-trivial conditions (see Zou, 2006 for details). In simple terms, an estimator possessing the oracle property will have the same asymptotic distribution for the coefficient estimates as the 'oracle' estimator, or in other words, the estimator is implemented knowing which coefficients are zero. This step allows an oracle estimator to be used not only for variable selection but also for inference. Nevertheless, implementing an adaptive amount of shrinkage for each regression coefficient leads to estimators that possess the oracle property (Zou, 2006; Wang *et al.*, 2007).

The adaptive LASSO can be formally defined as follows:

$$\hat{\beta}_{adapt}(\lambda) = \arg\min_{\beta} \left\{ \ell(\beta) + \lambda_{init}\lambda_{adapt} \sum_{j=1}^{p} \frac{|\beta_j|}{|\tilde{\beta}_{j,init}|} \right\}$$

where $\ell(\beta)$ is the corresponding loss function (in this case the negative log-likelihood for the logistic regression model), p is the number of parameters (to be estimated), $\tilde{\beta}_{j,init}$ is an initial estimate for the regression parameters, and λ_{init} is the penalty applied in obtaining this initial estimate. If the initial estimate is unpenalized, we set $\lambda_{init}=1$. In essence, the adaptive LASSO is a two-stage estimator, the second stage of which has the standard LASSO form. Here, we will follow Zou (2006) in using a standard unpenalized estimator (i.e., a logistic regression on all 102 variables) in the first stage, but any other estimator (such as e.g., standard LASSO) could be used instead.

To calculate the optimal amount of shrinkage applicable for the adaptive LASSO, path solution algorithms that calculate the path of solutions for a range of candidates for the amount of shrinkage are desirable. Such fast path solution algorithms are essential in the empirical application of the adaptive LASSO and other related shrinkage estimators. The theoretical results generally establish desirable properties, such as consistency and the oracle property. Such results, however, only hold under an appropriate choice of the shrinkage parameter that determines the amount of shrinkage applied to the parameters by the corresponding estimator. This choice requires two pre-requisites: a criterion for choosing the 'optimal' shrinkage and model estimates for a wide range of shrinkage parameters from which to choose the optimal one. The former is typically achieved either by some form of cross-validation or model-selection type of criteria, while the latter is the object of the path algorithms. By solving the underlying optimization problem for a range of shrinkage parameters simultaneously, these algorithms greatly reduce the computational load.

In this particular case, we have a logistic regression, which is a type of generalized linear model, characterized by implicit non-linearity. Here, we will implement the Local Quadratic Approximation (LQA) algorithm of Fan and Li (2001) and use 5-fold cross validation to choose the amount of shrinkage. From a purely computational point of view, the LQA algorithm is not as efficient as, e.g., the descent algorithms. It is, however, applicable to a much wider range of alternative types of penalties and allows us to compute comparable alternative estimators to implement robustness checks.

6. Results

We apply the adaptive LASSO to the logistic regression of the choice of Mzansi account on the set of 102 variables described in the data section. Table 2 presents the selected independent variables (i.e., the variables with non-zero coefficients) and their estimated coefficients. We present only the estimated coefficients. Confidence intervals can be obtained by bootstrapping the estimator (using, e.g., subsample bootstrapping). Alternatively, one may rely on the oracle property and obtain a conditional confidence interval by simply applying logistic regression to the selected subset of variables. Here, however, the focus of our analytical attention is the structure of the decision problem (i.e., which variables are important and what their effects are), and for simplicity of exposition, we will not present confidence intervals.

Of the 102 candidate variables, only 13 are retained in the estimated model. Here we briefly summarize the results. First, however, note the following details about the results interpretation. Because our variables are basically indicators, they are expressed in the same units, which mean the estimated coefficients are naturally 'standardized' in the sense that we can directly compare their magnitude. In this case, the strength of the relative effects will be directly proportional to the estimated coefficients. The most important and interesting estimation result and the focus of this investigation is which variables are retained in the model, as well as their relative contributions. In some cases, however, the fact that a given variable is not included in the final model (which indicates its lack of impact) could be an interesting and meaningful result in itself and could deserve attention.

We have also implemented a set of alternative estimators to check the robustness of the presented findings. Although alternative regularization-based variable selection methods select a slightly different subset of variables, the qualitative nature of the conclusions presented hereafter does not change with the method used. There are no sign reversals between the different estimation methods. Table 3 presents a qualitative comparison between the adaptive LASSO results presented in this paper (aLasso) and several alternative frequentist regularization methods, namely, the Smoothly Clipped Absolute Deviations (SCAD) method of Fan and Li (2001), weighted fusion (Daye & Jeng, 2009), the correlation-based penalty (Tutz & Ulbricht, 2009), OSCAR (octagonal shrinkage and clustering algorithm for regression) (Bondell & Reich, 2008) and the elastic net (Zou & Hastie, 2005), all of which were implemented via the LQA algorithm for comparability reasons. More efficient implementations exist and are outlined in an appendix. Table 4 presents a similar comparison with certain Bayesian methods, namely, Bayesian lasso (BL), Bayesian t shrinkage (Bt) and Bayesian Adaptive LASSO (BAL). Because Bayesian lassos have several different representations (see the technical appendix), it is important to specify the ones we applied. For the Bayesian lasso, we used the formulation of Yi and Xu. (2008). Popular alternative formulations are given in Griffin and Brown (2007), Park and Casella (2008) and Hans (2009; 2010). The Bayesian adaptive LASSO and the Bayesian T-shrinkage were implemented following Sun, Ibrahim and Zou (2010). A good overview of alternative Bayesian regularization priors is given in Fahrmeir, Kneib and Konrath (2010). Because, unlike their frequentist counterparts, Bayesian LASSOs do produce coefficient estimates that are identically zero, some (hard) thresholding is necessary to achieve variable selection. In Table 4, we present two different versions of such hard thresholding, labeled 1 and 2 to encompass both a liberal and conservative choice for the latter purpose. One may notice that the main results in the paper (e.g., aLasso) typically fall in-between these two choices). For ease of interpretation, the labels of the variables with negative effects in Tables 2, 3 and 4 are given in underlined bold typeface. Full results from these alternative estimators, as well as some other unreported estimators (e.g., several versions of Bayesian model averaging), are available from the authors upon request. The main purpose of these additional results is to demonstrate the robustness of our findings and interpretation, which we will not discuss in any detail. Without entering into too much detail, all methods chose similar variables, with certain methods replacing some of the variables selected by the lasso with one or more variables from the same group, which are amenable to similar interpretation. The reasons for these slightly different outcomes are technical and lie in the grouping properties of the different estimators and the way they handle correlated variables in small samples.

We now proceed to a discussion of the adaptive LASSO estimates (Table 2). First, the basic literacy variable does not discriminate between Mzansi account holders and non-holders. Because basic literacy can be expected to be a pre-requisite to any form of access to finance, it could be expected to be able to discriminate between individuals with and without such access. Note, however, that because the individuals without Mzansi comprise both people lacking access and people who use better accounts than the basic Mzansi access, such a variable cannot differentiate Mzansi holders from the rest.

Five variables from the "understanding of financial terms" category are retained in the model. Note that this category holds the most selected variables. Because all variables in this category are in essence different measures of the degree of financial literacy, this status is hardly surprising. The relationship of financial literacy with both personal characteristics and economic determinants (see e.g., Lusardi and Mitchell, 2013) explains why so many financial literacy measures are retained in our model. More specifically, the retained variables are as follows: Bad debt, Ombudsman, Interest rate capping, Debt counseling and Garnishee order or emolument order. Considering that this category has an almost natural hierarchy from simpler to more complex terms, the selected terms lie towards the lower end of this hierarchy. Considering the role of awareness (Bönte & Filipiak, 2012), in that not being aware of (or, here, not understanding) certain financial products can preclude access, one can view the above hierarchy as a proxy for the financial awareness of the respondents. It is thus logical that some basic awareness is necessary to step onto the access ladder. From this perspective, one can say that individuals choosing Mzansi only possess understanding of certain basic financial terms and thus have a minimal financial education/awareness. Such a basic understanding can be considered a pre-requisite for access to finance. We can go even further and state that the actual motivation to seek access to finance would require such a basic financial understanding, and then this motivation would lead to actively seeking financial services. If

Table 2. Estimation results

Variable	Coefficient
Intercept	0.638
Understanding of financial terms - Bad debt	0.102
Understanding of financial terms - Ombudsman	0.042
Understanding of financial terms - Interest rate capping	0.012
Understanding of financial terms – Debt counseling	0.067
Understanding of financial terms - Garnishee order or emolument order	0.072
Targets for financial advice - Independent broker	0.032
Financial education desired - How to make effective use of technology, such as cellphones or ATMs, to better manage your finances	-0.288
Financial education desired - How to determine how much credit you can afford/pay back	-0.196
Financial education desired – None	0.449
Financial perceptions grid 1 - As soon as money is deposited into your account, you withdraw it	0.352
Financial perceptions grid 1 - You go without basic things so that you can save	0.110
Financial perceptions grid 1 - If you don't have enough money to pay all your debts, you pay one debt one month, and the next month you pay another debt	0.033
Financial perceptions grid 1 - You have a will or last testament	-0.014

Table 3. Results from alternative frequentist estimation methods

	aLasso	SCAD	Weighted fusion	Correla-tion-based penalty	OSCAR	Elastic net
Understanding of financial terms - Bad debt	+	+		+	+	
Understanding of financial terms - Ombudsman	+	+				
Understanding of financial terms – FICA		+				
Understanding of financial terms - Interest rate capping	+	+				
Understanding of financial terms – Debt counseling	+	+		+		
Understanding of financial terms - Garnishee order or emolument order	+	+		+	+	
Targets for financial advice - Someone you trust in the community			+			
Targets for financial advice - Your employer			-			-
Targets for financial advice - Stokvel or umgalelo or savings club			-			-
Targets for financial advice - Independent broker	+		+	+	+	+

Table 3. Continued

	aLasso	SCAD	Weighted fusion	Correla-tion-based penalty	OSCAR	Elastic net
Targets for financial advice - A financial advisor other than an independent broker (e.g., tax consultant, auditor)			+	+	+	+
Targets for financial advice - Insurance company			+			+
Targets for financial advice - Other			-			-
Targets for financial advice - Teacher/Lecturer			-			-
Financial education desired - How to make effective use of technology, such as cellphones or ATMs, to better manage your finances	-	-	-	-	-	-
Financial education desired - How to determine how much credit you can afford/pay back	-	-	-	-	-	-
Financial education desired - How to select the best investment products					-	-
Financial education desired – Other			-		-	-
Financial education desired – None	+	+	+	+	+	+
Financial perceptions grid 1 - As soon as money is deposited into your account, you withdraw it	+	+	+	+	+	+
Financial perceptions grid 1 - You go without basic things so that you can save	+		+	+	+	+
Financial perceptions grid 1 - You hand over some or all of your money to a friend or family member for safekeeping or to guard it					-	
Financial perceptions grid 1 - If you don't have enough money to pay all your debts, you pay one debt one month, and the next month you pay another debt	+			+	+	+
Financial perceptions grid 1 - You have a will or last testament	-				-	
Financial perceptions grid 2 - When it comes to money, young people know more than older people					+	

Table 4. Results from alternative Bayesian estimation methods

	aLasso	Blasso1	Blasso2	Bt1	Bt2	BAL1	BAL2
Understanding of financial terms - Bad debt	+	+	+	+	+	+	+
Understanding of financial terms - Ombudsman	+						
Understanding of financial terms - Interest rate capping	+						
Understanding of financial terms – Debt counseling	+	+		+			
Understanding of financial terms - Garnishee order or emolument order	+	+	+	+	+	+	
Understanding of financial terms - Debt rescheduling		-					
Targets for financial advice - Independent broker	+						
Targets for financial advice - A financial advisor other than an independent broker (e.g., tax consultant, auditor)		+					
Financial education desired - How to make effective use of technology, such as cellphones or ATMs, to better manage your finances	-	-	-	-	-	-	-
Financial education desired - How to determine how much credit you can afford/pay back	-	-	+	-	-	-	-
Financial education desired – None	+	+	+	+	+	+	+
Financial perceptions grid 1 - You try to save regularly		+		+		+	
Financial perceptions grid 1 - You usually read the finance pages in newspapers and magazines		-		-			
Financial perceptions grid 1 - You are saving for something specific, for example, education, a holiday, an appliance or furniture		+		+			
Financial perceptions grid 1 - As soon as money is deposited into your account, you withdraw it	+	+	+	+	+	+	+
Financial perceptions grid 1 - You go without basic things so that you can save	+	+	+	+	+	+	+
Financial perceptions grid 1 - You hand over some or all of your money to a friend or family member for safekeeping or to guard it		-	-	-	-	-	-
Financial perceptions grid 1 - If you don't have enough money to pay all your debts, you pay one debt one month, and the next month you pay another debt	+	+	+	+	+	+	+
Financial perceptions grid 1 - You have a will or last testament	-	-		-		-	
Financial perceptions grid 1 - You find financial products that are provided by a local person to be cheaper than the products provided by a large organization		-					

Table 4. Continued

	aLasso	Blasso1	Blasso2	Bt1	Bt2	BAL1	BAL2
Financial perceptions grid 2 - When it comes to money, young people know more than older people		+	+	+	+	+	+
Financial perceptions grid 2 - You don't trust informal associations such as stokvels, umgalelos or savings clubs		-	-	-	-	-	
Financial perceptions grid 2 - You would allow monthly premiums or installments to be deducted from your prepaid cellphone account		-	-	-	-	-	

these individuals had possessed better financial knowledge, they would have opted for more advanced forms of access, from the basic entry accounts upwards. This interpretation is reinforced by the coefficients for the selected variables. Arguably, Interest rate capping and Ombudsman are at the top of the hierarchy for this category. Note that these two variables also have the smallest (in terms of magnitude) coefficients. Furthermore, two of the other three variables in this category, namely, Bad debt and Debt counseling, demonstrate that Mzansi participants pay particular attention to debt issues. Considering the size of the different coefficients, these debt-related variables account for approximately two thirds of the impact of this category. The understanding and the overall attention paid to debt issues suggest that Mzansi account holders could be worried about it (perhaps because they are experiencing or have experienced problems with debt) or could be generally debt averse. Such a suggestion is of course only a speculation for the moment, but it represents a workable hypothesis that can be examined in light of the results from the other categories or even be used as a basis for future studies.

There is only one selected variable from the category "targets for financial advice". Because the sample also contains individuals with no financial access and individuals with enhanced (compared to Mzansi) access to finance, the model finds it difficult to explicitly differentiate between differences that could be attributable to these two alternative categories. A major reason is that in contrast to the "understanding of financial terms" category, here it is difficult to find a similar natural hierarchy. It is also possible that the wording of the options within this category could be confusing for the respondents. The selected variable is Independent broker. Hence, one can say that the Mzansi holders seek independent financial advice. This result excludes family members and friends as well as the providers of financial services. One could assume that these (unselected) sources of financial advice are viewed as being more partial. Additionally, the Mzansi holders' existing basic financial understanding pushes them to seek some independence in making financial decisions. Their financial literacy being merely basic, however, means that they do not feel sufficiently confident in judging for themselves advice that can be viewed as being somewhat biased, and therefore, they prefer a truly independent opinion. Note, however, that as the coefficient for the variable under question is rather small, this type of quest for impartial financial advice is somewhat 'dormant' within the general Mzansi population. That dormancy should not, however, distract us from the importance of this finding. It may suggest that only segments of the Mzansi account holders exhibit such behavior, but such segments are of great interest to both banks (in that such people are the type of clients they desire) and to policy makers in that further investigation of such segments can provide important clues about how specifically to target financial access policy interventions.

The next category is "financial education desired". Our model includes three variables from this category. Seeking no further financial education makes one more likely to choose Mzansi. Thus, although Mzansi holders have reached a level of financial literacy (basic understanding), they do not try to move further up and are happy where they are. This result seems to confirm that Mzansi is situated at the frontiers of financial profitability from a banking point of view but also at the boundary of desire to access financial services.

The other two selected variables in this category make the decision to choose Mzansi less likely. This type of finding is expected because looking for further financial education expresses desires and aspirations that are typically inconsistent with basic financial access. Thus, such individuals would want to move further up the financial access ladder. This interpretation is reaffirmed by the type of these two variables. The first of these variables relates to the effective use of technology. This variable is a proxy for desire to move into other financial access channels, such as mobile banking. Note that such alternative banking channels may not necessarily be higher level accounts, but in the case of South Africa, they are likely to be more cost effective (less expensive) forms of access to finance. As already mentioned, this factor is most likely the main threat to the financial sustainability of Mzansi.

The other variable relates to working out credit repayments. This result could show a desire to overcome debt but also perhaps to plan for minor investments. Because there is a clear link between financial literacy and financial planning (Hastings et al., 2013), one might have expected that including a number of financial literacy variables might have already captured this effect. Note, however, that here we refer not to an ability but to an aspiration. The other important result is the size of the respective coefficients. By and large, the variables in this category exhibit the largest coefficients in terms of overall magnitude. Thus, the most important determinants of the self-conscious choice of the Mzansi intervention from an individual point of view are derived from the aspirations of the clients. Hence, who they want to be is much more important than who they actually are.

The final two categories address financial perceptions. An important result is that none of the variables from the second grid were selected. Considering that the second grid measures stated perceptions, as opposed to identifying perceptions revealed by their actual behavior in the first grid, this result may simply reflect an elicitation problem. The unreliability of stated as opposed to revealed preferences is by no means a novel fact. The selected revealed perception variables, however, show a very interesting story. There are four selected variables from this category. The first states that Mzansi holders generally agree with the statement (i.e., individuals agreeing with this statement are more likely to choose Mzansi) that money is to be withdrawn as soon as possible. This result is consistent with the known fact that many Mzansi accounts are used mainly for receiving payments. Furthermore, this variable has a sizeable coefficient, comparable with the coefficients in the previous category. Hence, in terms of importance, this attitude to using Mzansi mainly as a vehicle for receiving money is very important.

The other variables in this category, however, reveal a different type of motivation. The first two show a preference towards saving and general debt aversion amongst Mzansi holders. The preference towards saving is well defined (in terms of a sizeable coefficient), while the debt aversion effect is rather small. The latter should be placed in its wider context. Given the general debt awareness and the actual phrasing of the statement ("If you don't have enough money to pay all your debts, you pay one debt one month and the next month you pay another debt"), the small coefficients reflect an actual inability to achieve a debt reduction strategy rather than a lack of desire to do so. This result means that debt is viewed as a serious problem among Mzansi account holders. Therefore, the success of the Mzansi intervention may depend crucially on the general economic situation and on poverty alleviation measures that reduce the indebtedness of present and future customers. Both the above strategies (saving and debt aversion) show a tendency towards financial planning and a desire/aspiration for a lower discounting rate, i.e., a preparedness to move away from extreme forms of risk aversion that can lock individuals out of access to financial products. This result suggests that not everything is doom and gloom with Mzansi by hinting that it could, in principle, become sustainable for the banks from a financial point of view. Note, however, that this sustainability would only be possible if these preferences are realized, that is, if a sufficient share of the Mzansi population can afford to save and reduce indebtedness, which in turn depends on a number of other factors, such as economic growth. Furthermore, the relatively small (in magnitude) coefficients suggest that these offshoots of possible future financial sustainability are rather fragile and could be overshadowed by the present climate of financial austerity. This result is nevertheless important and deserves further investigation. The last variable may appear slightly counterintuitive. It refers to the fact that having a will makes one less likely to opt into Mzansi. What is counterintuitive is not the effect itself, which is rather logical, but the actual inclusion of this variable. This variable suggests a higher level of financial planning, which, logically viewed, would be characteristic of individuals with a better level of financial access. Hence, this variable distinguishes Mzansi 'from above'. Bearing in mind that its coefficient is very small, however, one should not attach to much significance to this particular result.

7. Conclusions

This study attempts to identify the underlying variables that distinguish users of Mzansi accounts from non-users. Drifting away from the body of literature that investigates supply-side determinants of access to finance, this research questions the assumption that willingness (a loose definition of demand) to access financial service is a given. The tools used to gauge willingness are perceptions and attitudes. In terms of perceptions, transactional demand for money was observed as the most important driving factor for possessing a Mzansi account, followed by savings and debt. The positive contribution of savings and debt preferences suggests that sustained employment schemes, for instance, can lead to an up-scaling of the financial demands of Mzansi account holders. Hence, the sustainability of holding the account actively depends on the extent of policy influence. The observation that Mzansi account holders seek information from independent financial advisors indicates the level of importance attached to verifying information received from traditional banking personnel. That is, financial literacy programs should be informed by a diversity of sources, financial desires and revealed perceptions.

There are certain inherent limitations to this study. First, we do not consider background variables, i.e., variables that could define the perceptions and attitudes. Such variables could, however, be added to our methodology to complement the characterization of the Mzansi choice. Furthermore, the cross-sectional nature of the data used only allows us to investigate static questions. Finally, the real choice is between Mzansi and other low-cost alternatives, which we did not consider in this particular application. Note, however, that all these limitations can be overcome in a subsequent study building upon the present results. After all, the characterization of the Mzansi choice, i.e., what exactly defines it, is a prerequisite for any such alternative explorations. Furthermore, applying the analysis to dynamic data or incorporating alternatives would create endogeneity issues, which cannot be reliably addressed unless the basic underlying structure of a decision problem is fixed. The methods in this paper achieve this task and therefore provide a reliable platform for such extensions.

References

Altman , M. (2012). Implications of behavioural economics for financial literacy and public policy. *Journal of Behavioral and Experimental Economics*, 41 (5), 677– 690.

Anand, M., & Rosenberg, R. (April, 2008). *Are We Overestimating Demand for Microloans?* Washington, D.C.: The Consultative Group to Assist the Poor.

Bankable Frontier Associates. (2010). *South African Financial Diaries and the Mzansi Initiative: Five Years Later*. Retrieved from http://www.finmark.org.za/wp-content/uploads/r_findiaries.pdf

Bauer M., Chytilova J., & Morduch J. (2012). Behavioral Foundations of Microcredit: Experimental and Survey Evidence from Rural India. *American Economic Review* 102 (2), 1118-1139.

Bauer, M. & Chytilová, J. (2009). *The Impact of Education on the Subjective Discount Rate in Ugandan Villages* (IZA Discussion Papers No. 4057). Institute for the Study of Labor.

Beck T., Demirguc-Kunt, A. (2008). Access to Finance: An Unfinished Agenda. *The World Bank Economic Review*, 22 (3), 383–396.

Beck, T., Demirgüç-Kunt, A., & Honohan, P. (2009). Access to Financial Services: Measurement, Impact, and Policies. *The World Bank Research Observer*, 24 (1), 119-145.

Białowolski, P., Kuszewski, T., & Witkowski, B. (2012). Macroeconomic Forecasts in Models with Bayesian Averaging of Classical Estimates. *Contemporary Economics*, 6 (1), 60-69.

Bondell, H. D. & Reich, B. J. (2008). Simultaneous Regression Shrinkage, Variable Selection and Supervised Clustering of Predictors with OSCAR. *Biometrics* 64 (1), 115–123.

Bönte, W. & Filipiak, U. (2012). Financial literacy, information flows, and caste affiliation: Empirical evidence from India. *Journal of Banking & Finance* 36 (12), 3399–3414.

Claessens, S. (2006). Access to Financial Services: A Review of the Issues and Public Policy Objectives. *World Bank Research Observer*, 21 (2), 207-240.

Cole, S., Sampson, T., & Zia, B. (2011), Prices or Knowledge? What Drives Demand for Financial Services in Emerging Markets?. *The Journal of Finance,* 66 (6), 1933–1967.

Daye, Z. J., Jeng, X. J. (2009). Shrinkage and model selection with correlated variables via weighted fusion. *Computational Statistics and Data Analysis*, 53 (4), 1284-1298.

de Janvry, A., Cai, J., & Sadoulet, E. (2012). *Social Networks and the Decision to Insure* (Working Paper). Goldman School of Public Policy, University of California, Berkeley. Retrieved from http://are.berkeley.edu/~esadoulet/papers/SocialNetwork_081612.pdf

Dohmen, T., Falk, A., Huffman, D., & Sunde, U. (2010). Are Risk Aversion and Impatience Related to Cognitive Ability?, *American Economic Review*, 100 (3), 1238-1260.

Dupas, P. & Robinson, J. (2013) Why Don't the Poor Save More? Evidence from Health Savings Experiments, *American Economic Review*, 103 (4), 1138-1171.

Fafchamps, M., McKenzie, D., Quinn, S. R., & Woodruff, C. (2011). *When is capital enough to get female microenterprises growing? Evidence from a randomized experiment in Ghana* (Working Paper No. 17207). National Bureau of Economic Research.

Fahrmeir, L., Kneib, T., & Konrath, S. (2010) Bayesian regularisation in structured additive regression: A unifying perspective on shrinkage, smoothing and predictor selection. *Statistics and Computing*, 20 (2), 203-219.

Fan, J., & Li, R. (2001), Variable selection via nonconcave penalized likelihood and its oracle properties, *Journal of the American Statistical Association*, 96 (456), 1348-1360.

Feigenberg, B., Field, E., & Pande, R. (2013). *The Economic Returns to Social Interaction: Experimental Evidence from Microfinance* (Working paper February 23). Harvard University. Retrieved from http://econ.duke.edu/uploads/media_items/feigenberg-field-pande-restud-02-13.original.pdf

Foss, N. J. (2012). Linking Ethics and Economic Growth: a Comment on Hunt. *Contemporary Economics*, 6 (3), 4-9.

Griffin, J. and Brown, P. (2007). *Bayesian adaptive lassos with non-convex penalization* (CRiSM Paper No. 07-2v2). Centre for Research in Statistical Methodology. Retrieved from http://www2.warwick.ac.uk/fac/sci/statistics/crism/research/paper07-2/07-2wv2.pdf

Hans, C. (2010). Model uncertainty and variable selection in Bayesian lasso regression. *Statistics and Computing*, 20 (2), 221-229.

Hans, C. (2009). Bayesian lasso regression. *Biometrika*, 96 (4), 835-845.

Hastings, J. S., Madrian, B. C., & Skimmyhorn, W. L. (2013). Financial Literacy, Financial Education, and Economic Outcomes. *Annual Review of Economics*, 5, 347 -373.

Hunt, S. D. (2012). Trust, Personal Moral Codes, and the Resource-Advantage Theory of Competition: Explaining Productivity, Economic Growth, and Wealth Creation. *Contemporary Economics*, 6 (2), 4-19.

Ito, S., & Kono, H. (2010). Why is the Take-up of Microinsurance so low? Evidence from a Health Insurance Scheme in India, *The Developing Economies* 48 (1), 74–101.

Karlan, D. & Morduch, J. (2010). Access to Finance, In D. Rodrik and M. Rosenzweig (Eds.), *Handbook of Development Economics* (Vol. 5) (pp. 4703-4784). Amsterdam: North Holland.

Lusardi, A., & Mitchell, O. S. (2013). *The Economic Importance of Financial Literacy: Theory and Evidence* (Working Paper No. 18952). National Bureau of Economic Research.

McCullagh, P., & Nelder, J. A. (1989). *Generalized Linear Models* (2nd ed.). London, UK: Chapman and Hall.

Meagher, P., & Wilkinson, B. (2002). *Filling the Gap in South Africa's Small and Micro Credit Market - An Analysis of Major Policy, Legal and Regulatory Issues* (Working Paper No. 02/11). University of Maryland.

Park, T., & Casella, G. (2008). The Bayesian Lasso. *Journal of the American Statistical Association*, 103 (482), 681–686.

Sun, W., Ibrahim, J. G., & Zou, F. (2010). Genome-wide Multiple Loci Mapping in Experimental Crosses by the Iterative Adaptive Penalized Regression. *Genetics,* 185 (1), 349-359.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso, *Journal of the Royal Statistical Society* B, 58 (1), 267-288.

Tutz, G., & Ulbricht, J. (2009). Penalized Regression with Correlation Based Penalty. *Statistics and Computing,* 19 (3), 239-253.

Wang, H., Li, R., & Tsai, C. L. (2007). Regression coefficient and autoregressive order shrinkage and selection via lasso. *Journal of Royal Statistical Society: Series B*, 69 (1), 63-78.

Yi, N., & Xu, S. (2008). Bayesian LASSO for Quantitative Trait Loci Mapping. *Genetics*, 179 (2), 1045–1055.

Zou, H. (2006). The adaptive lasso and its oracle properties. *Journal of the American Statistical Association*, 101 (476), 1418-1429.

Zou, H. & Hastie, T. (2005). Regularization and Variable Selection via the Elastic Net. *Journal of the Royal Statistical Society: Series B*, 67 (2), 301-320.

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